

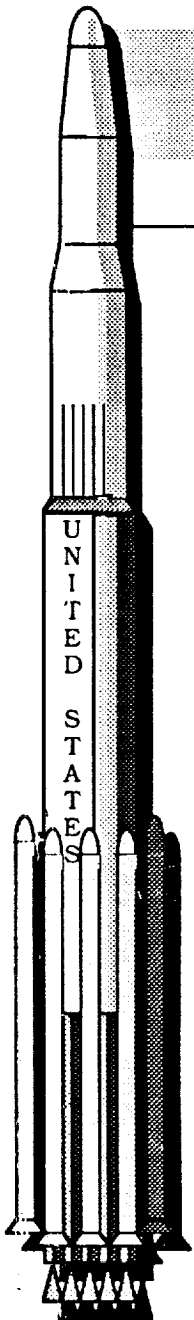
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Center for Advanced Space Propulsion



**ENGINEERING MONITORING EXPERT
SYSTEM'S DEVELOPER**

FINAL REPORT

August, 1989 - December, 1990

for

**Phase I
and
Phase I Extension**

**NAG2-596
&
NAG2-596-Supplement 1**

by

C.F. Lo, P.I.

February, 1991

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CASP

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PREFACE

The work presented herein was conducted by the University of Tennessee Space Institute, Tullahoma, TN under the NASA Research Grants No. NAG 2-596 and NAG 2-596-Supplement No.1. The results of the research were obtained under the direction of Principal Investigator Dr. Ching F. Lo, Professor of UTSI. The other contributors include Dr. Z. Shi, Research Engineer, CASP of UTSI and Dr. H.H. Liu, Associate Professor of Vanderbilt University. The NASA Technical Officer for this Grant is Dr. Frank W. Steinle, Jr., Aerodynamic Facilities branch, 227-5, NASA/ARC, Moffett Field, CA 94036. The research was performed from August, 1989 to December, 1990, and the manuscript of this final report was submitted for publication on February 15, 1991.

1. INTRODUCTION

1.1 Summary

This research project is designed to apply artificial intelligence technology including expert systems, dynamic interface of neural networks, and hypertext to construct an expert system developer. The developer environment is specifically suited to building expert systems which monitor the performance of ground support equipment for propulsion systems and testing facilities. Monitoring data will be acquired on-line through a set of measurement sensors. A dynamic database will be generated by conventional data processing techniques and/or a neural network interface module. The expert system developer, through the use of a graphics interface and a rule network, will be transparent to the user during rule constructing and data scanning of the knowledge base. The project will result in a software system that allows its user to build specific 'monitoring type' expert systems which monitor various equipments used for propulsion systems or ground testing facilities and accrues system performance information in a dynamic knowledge base. The resulting expert system developer at the end of the project has great potential for improving productivity in the construction of monitoring expert systems.

The specific area which was chosen as an example to demonstrate and develop the general expert system developer is Compressor Stall Monitoring system. This resulted sample monitoring expert system can be implemented for its own usage.

1.2. Technical Objective

The objective of this research project is to design and construct an Expert System Developer (or shell) specifically for building equipment monitoring expert systems. Users can employ the Developer to build an expert system in which the knowledge base links directly to processed sensor processing through conventional techniques and neural networks.

The objectives of Phase I are to design the architecture of the expert system, to identify the appropriate areas, and to implement acquired data processing methods including conventional and neural networks algorithms.

In Phase I-Extension, the construction of a prototype Expert System is to be initiated which links the data processing facility constructed in Phase I to the knowledge base. A system executive is to be built to manage all the elements as well as to feed the output of conventional pattern recognition algorithm and neural network to the expert system. The prototype expert system should be demonstrated to show its feasibility.

2. PHASE I RESULTS

The topic of stall monitoring of the AEDC 16-Foot Transonic/Supersonic (16T/S) compressor has been identified as the specific area to be studied for the future construction of expert systems developer. The architecture of the expert system development environment has been designed. The neural networks model and conventional pattern recognition paradigm for classification have been investigated and selected. In Phase I-Extension, a prototype expert system for the purpose of demonstration has been implemented on the PC/MS-DOS platform successfully using the 16T/S compressor data.

2.1. Topic Identification

In order to create an Expert System Developer, it has to start to construct specific expert systems of some selected typical topics. In the area of test facility operation, the continuous monitoring system is mostly concerned either the performance or the mechanical vibration of the rotating machinery. Thus, the following two specific areas which are the similar type problems existing at NASA/ARC and AEDC/AF have been considered to be investigated.

2.1.1. Compressor Stall Monitoring

The stall monitoring for the compressor in the AEDC 16-Foot Transonic/Supersonic (16T/S) wind tunnel was considered as the first candidate of the selections. The primary monitoring data are based on the time traces of rotor blade stresses during the operation of 16T/S compressors. The sensors data are recorded in the Compressor Monitoring System disk records and Compressor Monitoring Room oscillograph traces as shown in Figure 1. An early stall warning and detection expert system is intended to be constructed utilizing these time traces data and other auxiliary facility parameters.

2.1.2. Vibration Analysis for Rotating Equipment

The Vibration Analysis for Rotating Machinery in the Engine Test Facilities at AEDC was considered as the second candidate of the selections. The system should improve maintenance program based on machinery condition as diagnosed by vibration analysis. The ultimate goal is to reduce the dependence on specialists in vibration analysis and to transfer the first level of diagnosis of problems to plant personnel.

The topic of stall monitoring of the 16T/S compressor has been selected to study first, because the format of the data and the support from domain experts are readily available for immediate usage. These are the critical issues to justify the initiation of this study. The area of the vibration analysis for rotating machinery in the Engine Test Facilities at AEDC was deferred for the future application.

2.2. Monitoring Expert System Architecture

A monitoring expert system architecture has been designed consisting of three major subsystems: knowledge-based diagnostic subsystem, neural network subsystem, and conventional algorithm data analysis subsystem. Figure 2 shows the relations between these subsystems.

Sensor signals usually require some type of preprocessing such as digital-to-analog conversion and filtering before they are submitted to data analysis and feature extraction.

The conventional data analysis subsystem utilizes conventional frequency spectrum, waveform and statistical techniques for data and pattern recognition analysis. This part is comprised largely of well established engineering analysis techniques. Results of data analysis are applied to the knowledge-based subsystem which is responsible for symbolic reasoning of the diagnostic process.

The neural network subsystem extracts useful features and classifies data patterns. Neural networks can be trained by examples and are more tolerant to noise. Such networks should be used in conjunction with conventional techniques to enhance the problem solving capability.

The knowledge-based subsystem employs heuristic knowledge such as rules acquired from domain experts for problem solving.

2.3. Testing Data Acquisition and Process

The primary monitoring data are based on the time traces of rotor blade stresses during the operation of 16T/S compressor. The data of Normal run for rotors and stators of Compressor C-1 of 16T at AEDC were recorded for various flow conditions. The flow Mach Number covered includes 0.6, 0.9, and 1.2. The original data from stress sensors were recorded on the magnetic tape in the analog format. The Rotor stress data include sensors A13 (for Rotor A and sensor #13), A17, B1, B2, C16, and C17. The Stator stress data include sensors S1, S2, and S4. The rotor and stator locations of Compressor C-1 are shown in Figure 3.

The analog data were converted to the digital format by a commercial program named STAR System (Ref. 1) and the spectrum analysis in frequency domain was also carried out by the STAR system. With the output binary data by STAR, a program for data reading and plotting was implemented on the PC. The resulted typical frequency spectrum data for A13 and C17 at Mach Number 0.6 are shown in Figure 4. More than 50 sets of digital data of amplitude vs. frequency for each sensor were converted for utilizing in the techniques of Neural Network and Pattern Recognition.

2.4. Simulator for Compressor Rotor/Stator Stress Data

For the rule-based expert system as well as neural network process, it is required to acquire sufficient data samples under normal and abnormal operating conditions, specially under the stall conditions. Since the most operation of 16T/S compressor is under normal condition, the stress data for the normal condition are relatively easy to be acquired. On the other hand, the data under stall condition are very limited. It is not advisable to force the compressor to enter stall situation to acquire such data. The alternative is to create a numerical Simulator which may provide those stall dynamic stress data. It is apparent that this simulator becomes necessary to generate such stall conditions data which otherwise would not be available. Therefore, the task to built a Simulator to produce the signals of dynamic stress data was completed in this phase.

The Simulator is basically the superposition of several sinusoidal, for example, sine waves form at various amplitudes, frequencies, and phase angles. Amplitudes (coefficients), frequencies and phase angles of sine waves are determined from the actual analog spectrum or, if necessary, from expert's drawing. A Fortran code of fast Fourier transform algorithm has been adopted from the existing subroutine implemented for the simulator running on an IBM-PC. The first test case is the Compressor C1 at AEDC for the rotor's ``Normal'' and ``Rotating Stall'' operation conditions. The results are very satisfactory. The rotating stall is based upon domain expert description to simulate the input data.

Another method to simulate rotational stall data has also been developed. The simulator starts from the Rotor Normal data and then incorporates inputs symptoms of rotational stall which are supplied by "domain expert". The typical Simulated results are shown in Figure 5. These simulated data have been used to develop the expert system until the real test data are obtained in the future.

2.5. Neural Network Models for Classification

2.5.1 Evaluation of Neural Network Software

The neural network software evaluated was the NeuralWorks from NeuralWare, Inc (Ref. 2). This software package seems to be quite appropriate for the project needs. First, it runs on several platforms ranging from PC, Macintosh to Sun workstation to even N-Cube parallel computer with the same network specifications. Networks can be constructed using either the InstaNet facility or the Network Editor. Over one dozen well known networks such as Perceptron, Hopfield, Back-Propagation, and BSB are available as standard networks in InstaNet to facilitate quick prototyping. Users can define any customized networks using Network Editor. One can define the specific processing elements (PE) including transfer function and learning rule. Layer is made of processing elements, and network is made of layers and connections. Control strategy can be specified for the entire network for both learning and recall.

Input/output can be done through either keyboard or file; file I/O will be more useful for the present application. The entire system of NeuralWorks is menu-driven, interactive and has plenty of graphic supports. It is rather versatile, powerful and easy-to-use. The overall evaluation about NeuralWorks is very good, and the decision has been made to use this package for the project.

2.5.2 Network Architecture

A three-layer back-propagation (BP) network (Ref. 3) has been selected for classification of air compressor operation conditions. The multi-layer BP networks have been studied extensively and widely used for hetero-association and pattern classification. Multi-layer networks are able to classify non-linearly separable classes. Back-propagation is the technique selected to solve the present problem. That is, the errors due to misclassification will be properly distributed to and rectified by all the connecting weights. In the present case, a three-layer, input layer, hidden layer and output layer, network is utilized as illustrated in Figure 6. The input layer takes the peak amplitude of stress frequency spectrum as feature inputs and sends them to the hidden layer. There are presently 11 nodes at the input layer representing 11 major peaks of frequency spectrum, 3 nodes at the output layer representing normal, near stall and deep stall condition of the air compressor, and 6 nodes at the hidden layer. Using NeuralWorks, the number of nodes, configuration and other parameters can be changed rather easily. The data from Row B of C3 Rotor Blade were supplied by Calspan/AEDC and chosen to investigate the BP since the data are available for three distinguished conditions--normal, near stall and deep stall.

2.5.3 Learning and Recall Procedure

Learning: Three frequency spectra for normal, near stall and deep stall conditions from Row B of C3 Rotor Blade were used for training the neural network. The network converged very quickly and the network classified the original training patterns correctly. The input/output file was set up as follows where i stands for input and d stands for desired output:

Training data for C3 Rotor Blade Row B. Data were taken from actual stress frequency spectra.

i	0.3800	0.4500	0.4800	0.5300	0.3800	0.3600	0.2200
	0.1600	0.1500	0.3500	0.0300			
d	1.0	0.0	0.0				
i	0.4700	0.4700	0.3700	0.4300	0.2800	0.4000	0.3100
	0.2400	0.2700	0.4600	0.0800			
d	0.0	1.0	0.0				
i	0.1800	0.1400	0.0300	0.1200	0.0050	0.1400	0.0050
	0.0050	0.0050	0.5500	0.0800			
d	0.0	0.0	1.0				

Recall: Since there was no additional data for testing the neural network, some test data based on the original training data are generated. A 5% random noise with Gaussian distribution was added to the original normal, near stall and deep stall data. Three test samples are generated for each group. All nine test data were classified correctly. If the original training data are good representative of the underlying distribution, then this test shows quite excellent performance. The graphical display for the results shown in Figure 7 represents three layers: input, hidden and output layers. The size of rectangular symbol represents the magnitude of the value of each node. The output layer Symbol 19 indicates that this result is Normal run condition given in Figure 7a. The results of near stall and deep stall conditions are shown in Figures 7b and 7c.

Rotor C1 for both Normal and Rotating stalling conditions including data of Row A and Row C will be investigated in the next Phase.

2.6. Pattern Recognition Algorithm

The pattern recognition paradigm (Ref. 4) divides the procedure into two phases: training and test. The basic concept of the present pattern recognition paradigm is to recognize the feature vector and apply an algorithm called Nearest Neighborhood. The feature vector is a set of measurements which are utilized to condense the description of a set of properties into a Euclidean feature space of multi-dimensions. Each point in feature space represents a value for the feature vector applied to a different category. Ordinarily, during a training phase, feature vectors from known sample data are used to partition feature space into regions representing the different classes. During a test phase the feature space partition are used to classify feature vectors from unknown data.

2.6.1 Minimum-Distance Pattern Classification Method

First, all feature vectors are normalized to eliminate the absolute magnitude of each signal. The class-average vector is calculated from all feature vectors of a single class. Figure 8 shows three classes A, C and R in a two-dimensional (two features) hyperplane domain. The classification of the signal is based on the minimum distance from the signal vector to each class-average vector center (one center for each class). The test of each data set will examine the distance from the data signal vector to the center of each pattern class. The data signal will be classified as that specific class which the minimum distance occurs between the data signal and one of the class centers.

2.6.2 Clustering Method

The basic idea about the clustering method is that the given signals can be partitioned into multiple cluster domains. For each cluster, there is a cluster center (average of all the data in that

cluster). In each class, there are several clusters and each of them has a cluster center. The corresponding clusters centers become representatives of them. The determination of a given signal belonging to certain class is based upon the signal's relations to the multiple cluster's centers. The clustering method is preferred over the Minimum-Distance method (one center for each class), as mentioned in the previous section, of a single cluster in some cases. If the signals are evenly distributed over their regions, the two method are the same. But if the distributions are not perfectly even, one center cannot adequately represent its overall characteristics.

2.6.3 Cluster-seeking Algorithm

The Maximim (Maximum-Minimum)-distance algorithm is applied for cluster-seeking. This method is a heuristic procedure based upon the Euclidean distance concept. The algorithm consists of the following steps:

1. Arbitrarily choose a signal to be the center of the first cluster.
2. From the remaining signals, find that one whose distance to the first cluster is farthest and assign it to be the center of the second cluster.
3. For each remaining signals, calculate the distances to each center and store the minimum. Among all the minimum distances, choose the maximum. If the maximum (of the minimum group) is greater than one-half of the (largest) distances between centers, that signal becomes another center and then perform (3) again; otherwise the algorithm terminates.

After having the centers, each remaining signal is assigned to its nearest cluster center. To obtain a representative cluster center for each group, the mean of each cluster signals is designated as the new cluster center.

2.6.4 Cluster-Belonging Criteria

The Maximim (Maximum-Minimum)-distance algorithm for the cluster-seeking described above has been applied to the data sets of (A1306, R1306) and (C1706, R1306). Data of A1306 and C1706 were obtained from Row-A blade-13 and Row-C blade-17 at Mach Number 0.6 Normal running condition, respectively. Data of R1306 are Simulated Rotational stall condition at Mach Number 0.6. Four clusters (therefore four cluster centers) for A1306 sets of signals were obtained and five clusters for R1306. For a given signal, two cluster-belonging criteria have established as follows:

1. Among all (total nine for A1306 and R1306) distances for a signal to cluster centers such as (A1306, R1306), the minimum one decides the class which it belongs to (One-Minimum Nearest Neighbor).

2. The signal nearer to the distance average of cluster center belongs to the corresponding class (Distance to Cluster Centers Average).

2.6.5 Results of (A1306 vs R1306) and (C1706 vs R1306):

The above cluster-belonging criteria are applied to the classification of (A1306 vs R1306) and (C1706 vs R1306). The following results obtained are listed in Table 1. Criterion-1 (One-Minimum Nearest Neighbor) can get better overall results. Criterion-2 (Distance to Cluster Centers Average) yields reasonable good results. But there is no perfect way among the above two criteria to classify the signals. For the purpose of comparison, the Minimum-distance method of non-clustering method (one circle) also is applied to the present case. The results is very close to One-Minimum criterion.

In general, the experience has shown that any reasonable methods will work for a good physical features. It is critical to select a good representative features of a physical problem. The feature vector selected for the current problem is the same as those in the neural network: the peaks of amplitude at various frequencies. Similarly the results should be obtained as expected.

3. PHASE I-EXTENSION RESULTS

3.1 Prototype Monitoring Expert systems

A prototype Monitoring Expert System has been implemented on the IBM PC platform. The basic elements of this system are shown in Figure 9. A spectrum analyzer for fast Fourier transform is used to process the sensor data from time-domain to frequency-domain by applying a commercial program, STAR. A feature extraction has developed in Quick Basic code to extract the characteristics from the resulted spectrum data. The test-data sets are then classified by a commercial neural networks shell, NeuralWorks, or by a conventional pattern recognition based on the weights and database template which were pre-trained in neural networks and pattern recognition from the data feature characteristics. The knowledge base and inference engine are contained in a commercial expert system shell, Level5 (Ref. 5). The function of the expert system is to supply advice and relevant information for the end-user to correct the problem. A graphic display program provides the user to examine the data characteristics.

A system executive (user interface) has been constructed to manage all the key elements including data processing, conventional pattern analysis, Neural Network, expert system, etc. This executive is built on a Hypertext software, Guide 3.0 (Ref. 6), which has excellent display ability and a high level programming language. From the Main-Menu shown in Fig. 10, the user can directly launch (execute) the desired item by clicking on its image. The inner link will follow the pre-designed order to complete the specific task. A brief description of each task in Fig. 11 is given below.

A click at the "Data input" will bring a dialogue box to ask for the input test-data file name and then open the specified file for testing. The "Graphical Display" will display the plot of the test-data set in the frequency domain when the user requests to examine it. The "Feature extraction" extracts the critical peak amplitudes of stress spectrum of this data set. The "Conventional data/pattern analysis" and "Neural Network" are utilized to test and classify the test-data by calling the conventional pattern recognition program and NeuralWork respectively. Finally, an expert system can be called in to display the analyzed result, give warning if the compressor is near stall or already stall, and provide advice to the user to correct the problem. The expert system directly reads the output from either the Neural Network or the conventional pattern recognition program whichever the user has selected for the last running. Text and graphical information will be stored in hypertext format and can be retrieved easily.

The demonstration expert system which links output from the Neural Network or the conventional pattern recognition has been constructed on the limited knowledge base in the present time to check the architecture of the proposed expert system. A list of software is included in Appendix A. The codes of the software on a 5¹/₄ diskette are delivered to the technical officer only.

3.2 Automatic Operation Mode

The above described operation is designed for users having the complete control to select any specific task to show the feasibility of the integration. An automatic operation of these tasks will be added later. The automatic mode will ask the user necessary questions such as the input test-data file name, the test-data classification method at the beginning of the operation and then execute the tasks continuously without users interaction. The result of monitoring data classification and some recommendation or advice will display in the text and graphic format at the end of the sessions. This automatic operation mode is being planned to be implemented in the next Phase.

4. CONCLUDING REMARKS AND FUTURE WORK

A prototype neural network based expert system has been implemented in commercial tools for the demonstration purpose. The proper selection or combination of Neural Networks and conventional pattern recognition could result in optimal data processing procedures for the expert system.

The acquisition and refinement of the knowledge base for the expert system are required to in the next phase. Furthermore, the additional flow variables of the compressor such as the flow Mach number, stagnation pressure, stagnation temperature as well as the sensor data should be input directly in the expert system's data base to support the compressor condition monitoring and diagnoses.

In the future work, it appears feasible and beneficial to develop a generic monitoring expert system which would be extended to an expert system developing environment and which, in turn, would be used for constructing other specific expert systems.

ACKNOWLEDGEMENT

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TABLE I

A1306 vs. R1306

The initial point is the one of un-normalized farthest point from the origin.

(The clustering approach finds 4 groups in A1306, 5 groups in R1306.)

The radius of A1306 is 0.868789.

The radius of R1306 is 0.969805.

The distance between two circles is 0.322254.

	One minimum Nearest Neighbor	Distance to Cluster Centers Average
A1306	0 (100%)	0 (100%)
R1306	-1 (98%)	-5 (90%)

Remark: the minus means misclassification number.
 the percentage in the bracket means correct rate.

C1706 vs. R1306

The initial point is the one of un-normalized farthest point from the origin.

(The clustering approach finds 5 groups in C1706.)

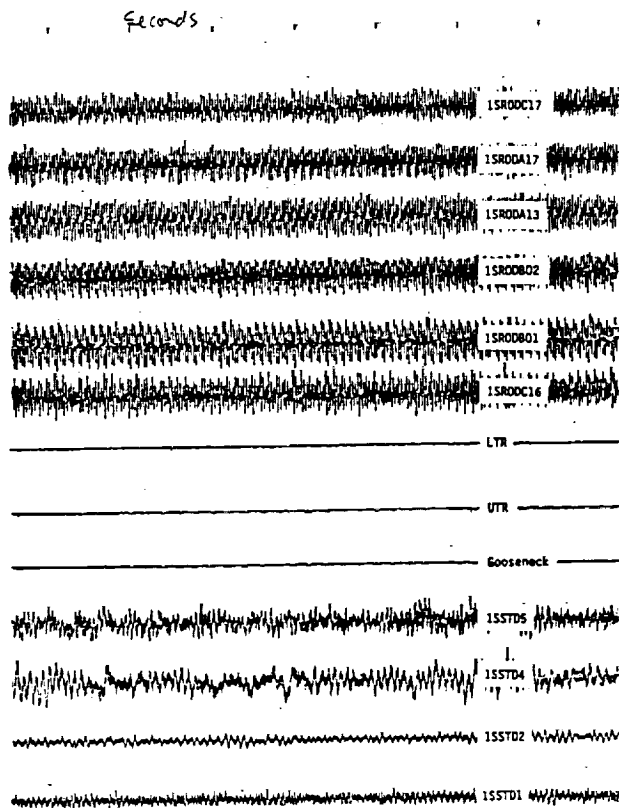
The radius of C1706 is 0.867510.

The radius of R1306 is 1.036084.

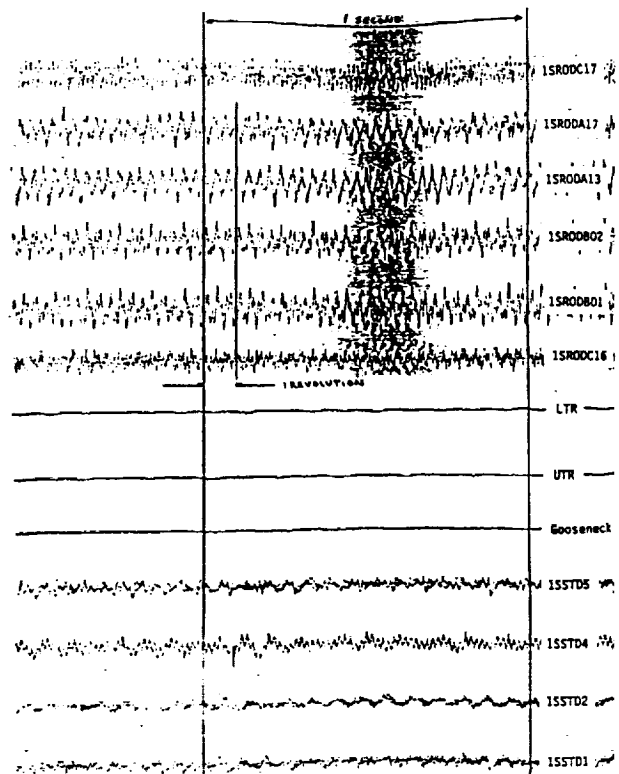
The distance between two circles is 0.433841.

	One minimum Nearest Neighbor	Distance to Cluster Centers Average
C1706	0 (100%)	-4 (93%)
R1306	-2 (96%)	-4 (92%)

Remark: the minus means misclassification number.
 the percentage in the bracket means correct rate.



(a). 25 mm/sec



(b). 100 mm/sec

Figure 1. Typical C1 stress traces.

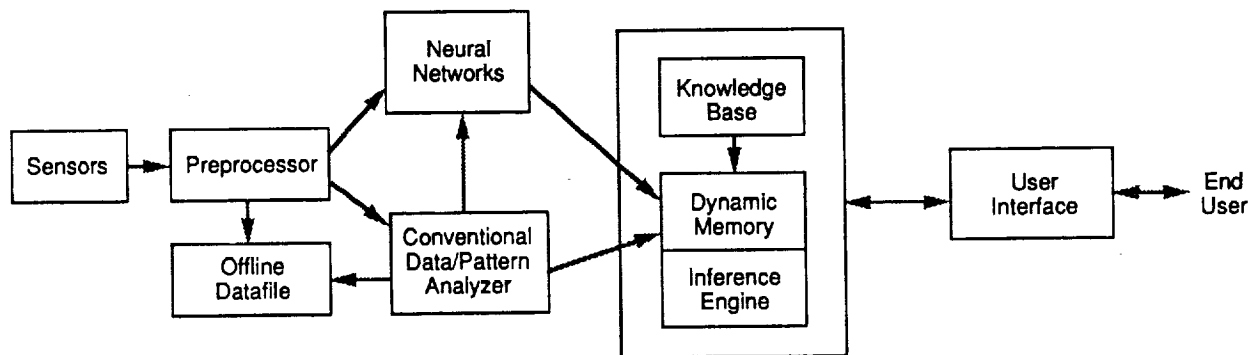
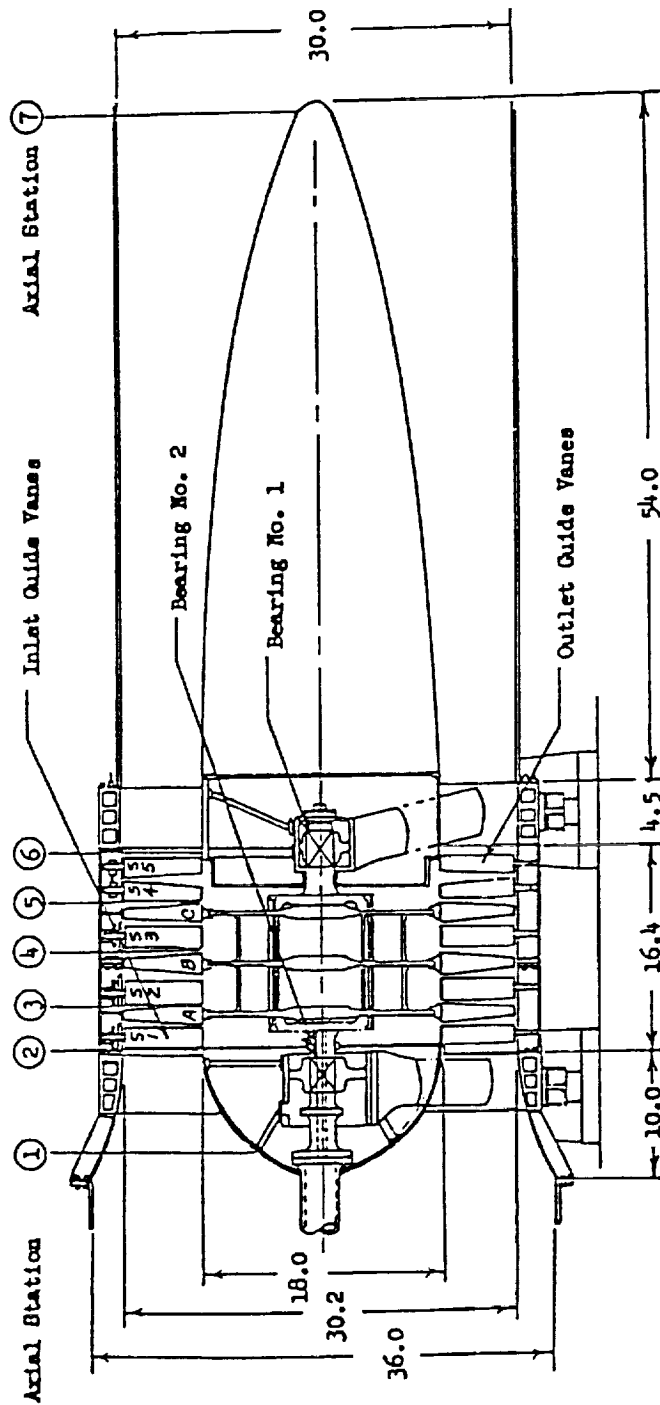


Figure 2. The architecture of an Engineering Monitoring Expert System.

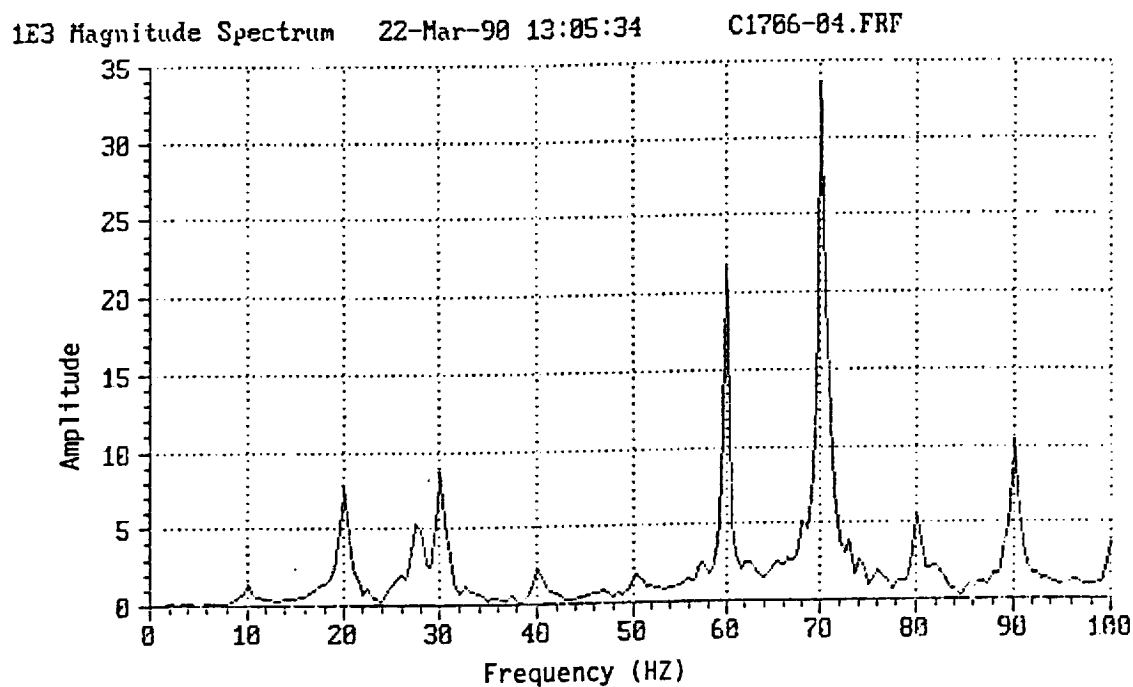


Design Conditions

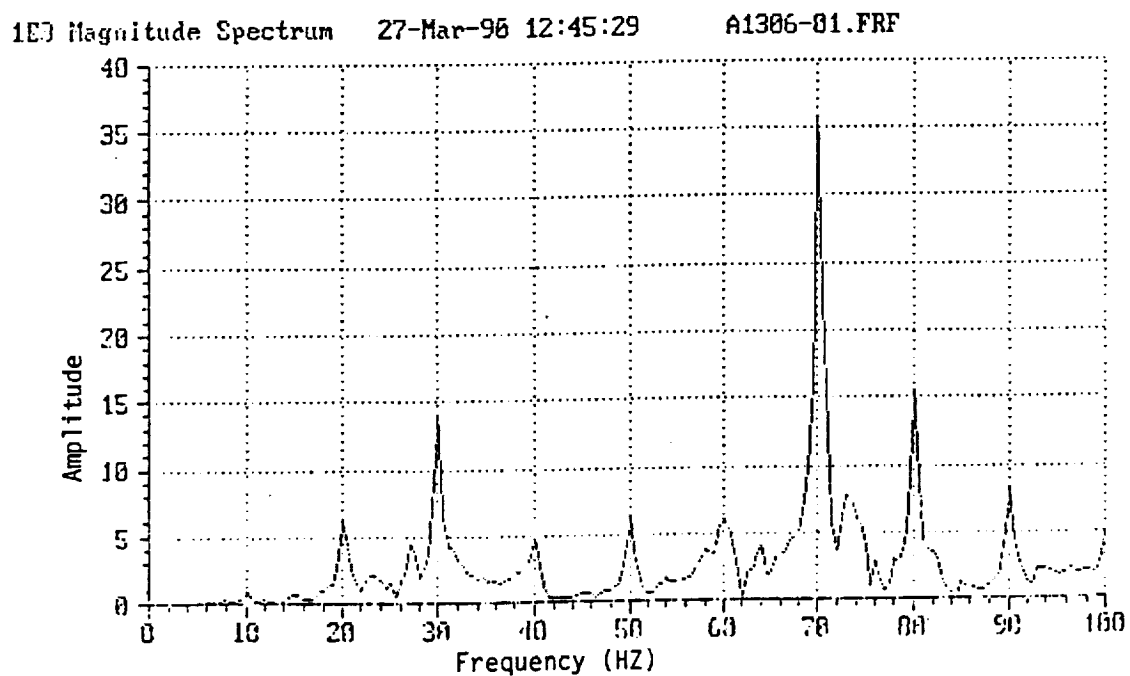
Tip Speed 942 ft/sec (Absolute)
 Hub Speed 565 ft/sec (Absolute)
 Design Pressure Ratio 1.385
 Design Inlet Volume Flow 200,000 cfs
 Flow Coefficient 0.47
 Work Coefficient 0.308
 Inlet Axial Velocity 442 ft/sec

All Dimensions in Feet

Figure 3. Dimensions for Compressor C1.



(a). Rotor C, Sensor C17, M=0.6



(b). Rotor A, Sensor A13, M=0.6

Figure 4. Typical frequency spectrum data plot.

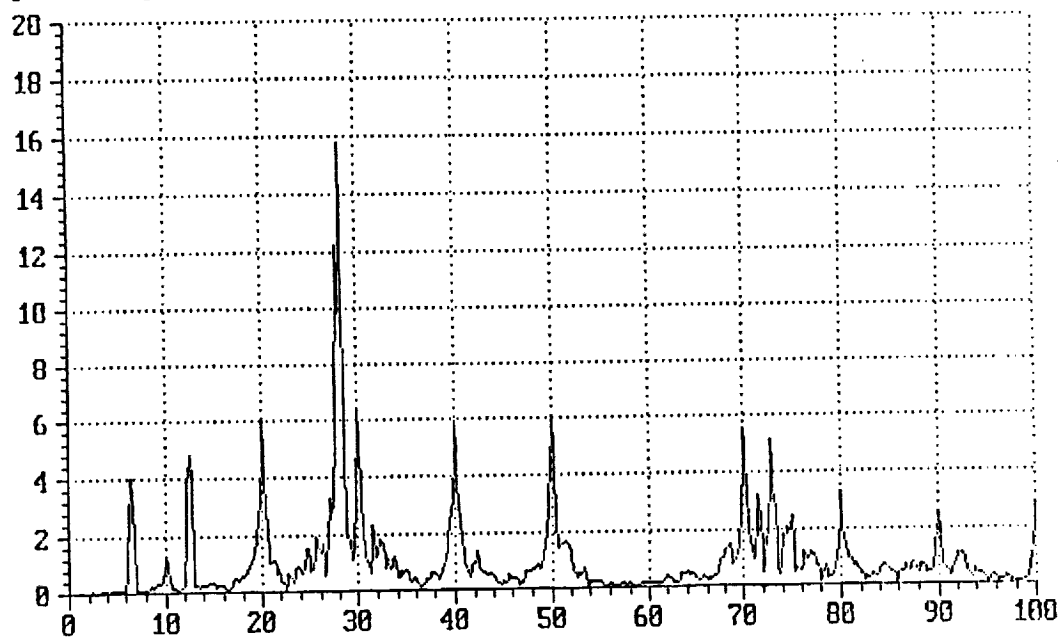


Figure 5. Simulated frequency spectrum data for rotational stall.

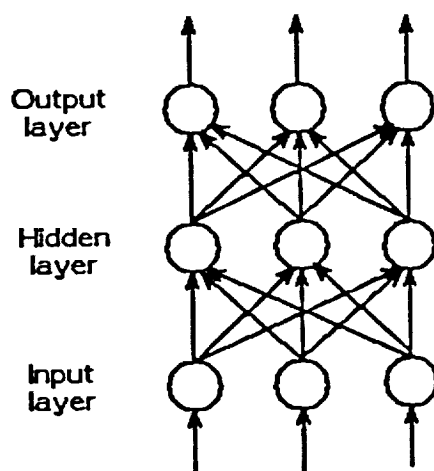
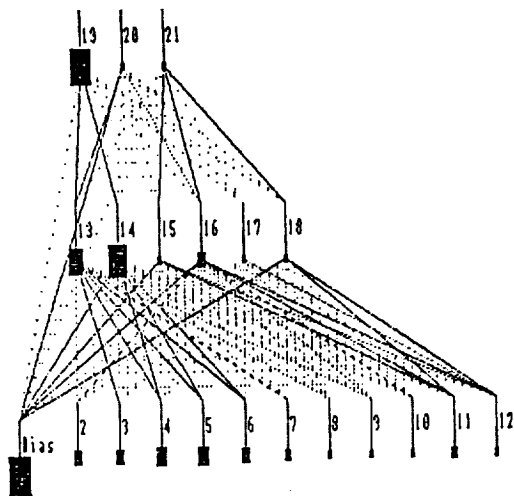


Figure 6. A Neural Network model with full connection.

□ Rotor Blade Row B

Normal run condition

NeuralWorks results for blade stress spectrum

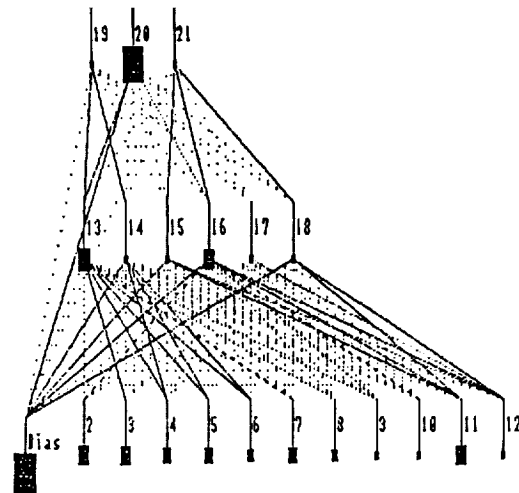


(a). normal running condition

□ Rotor Blade Row B

Near Stall Condition

NeuralWorks results for blade stress spectrum

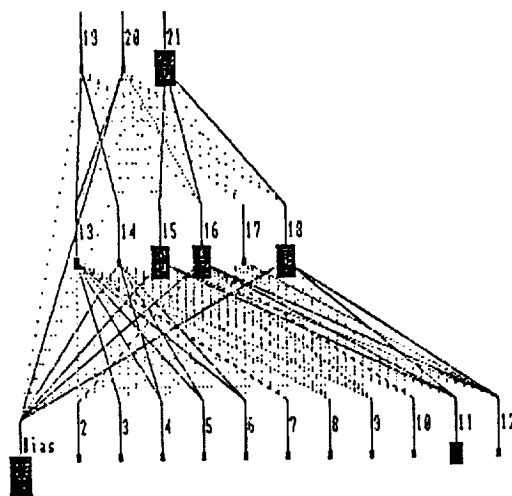


(b). near stall condition

□ Rotor Blade Row B

Deep Stall Condition

NeuralWorks results for blade stress spectrum



(c). deep stall condition

Figure 7. A three-layer BP Network for rotor blade row B

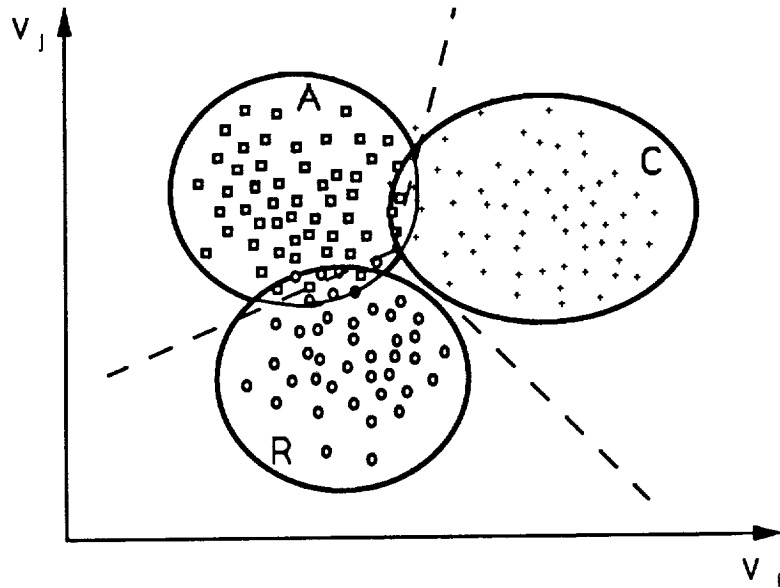


Figure 8. Pattern classification regions.

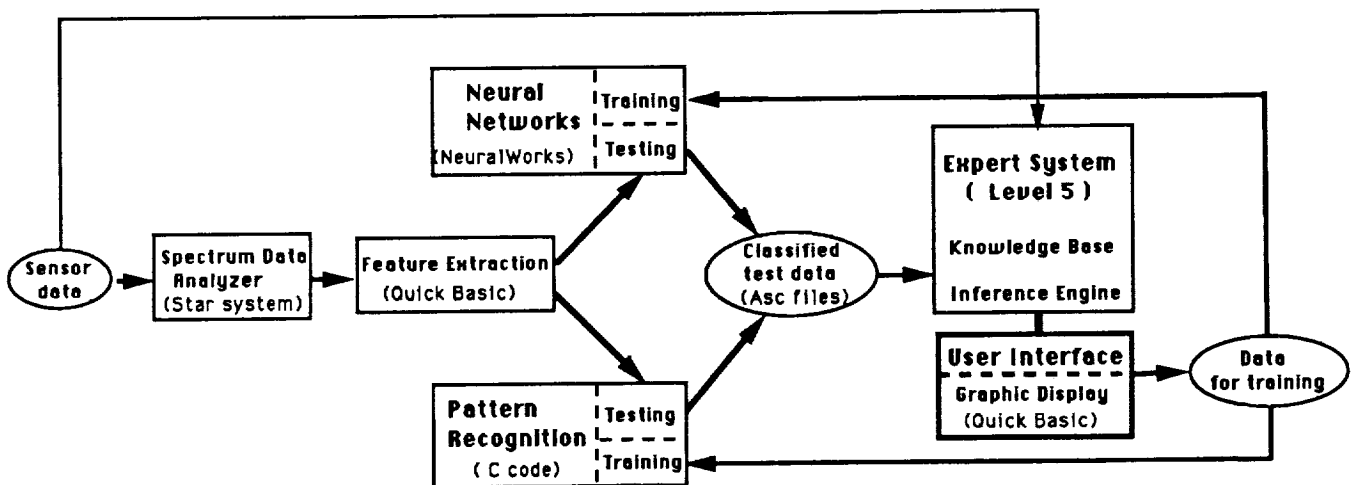


Figure 9. Architecture of the prototype Compressor Stall Monitoring Expert System.

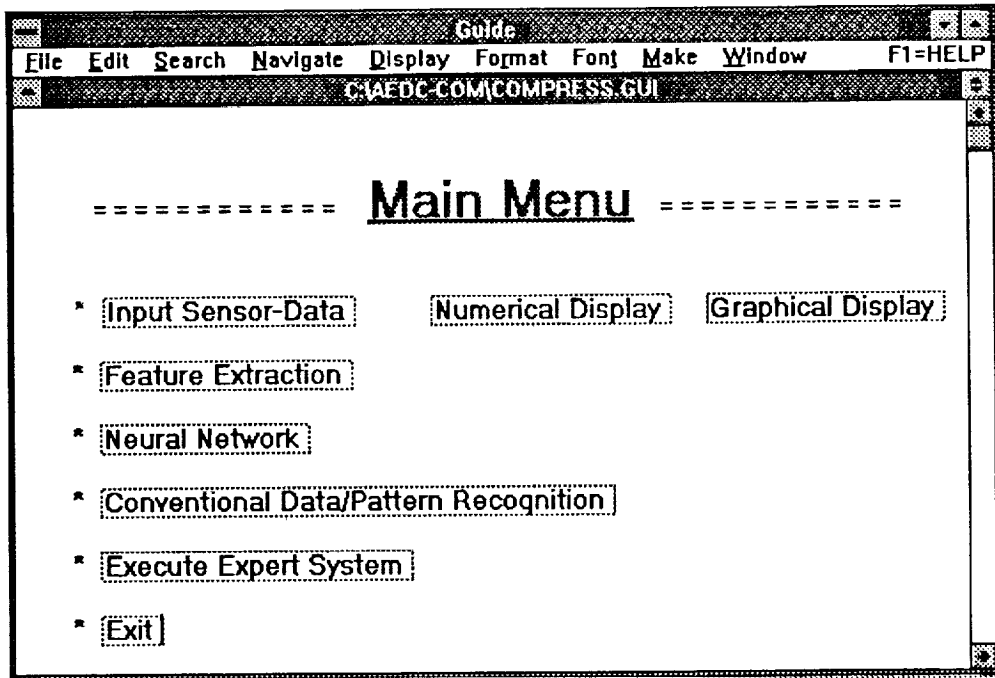


Figure 10. Main-Menu of the demonstration prototype Compressor Monitoring Expert System.

Main Menu

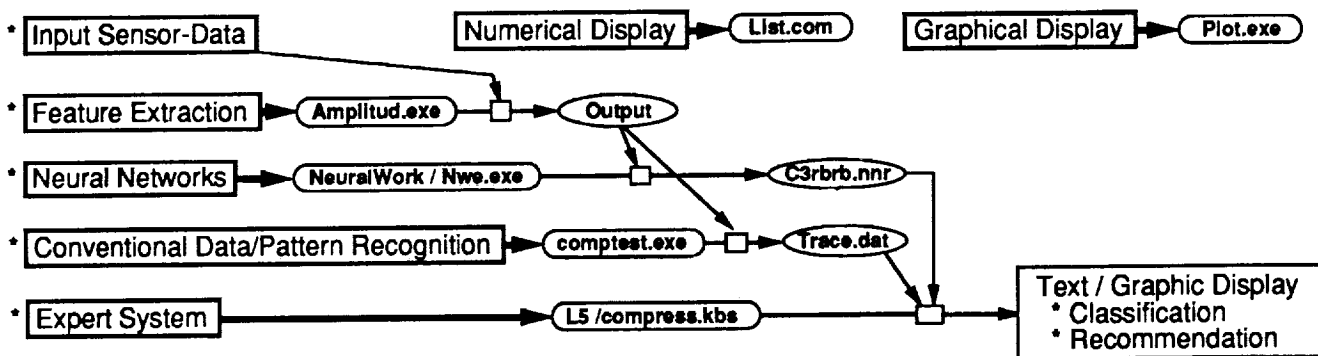


Figure 11. Integration of various tasks in the prototype Expert System.

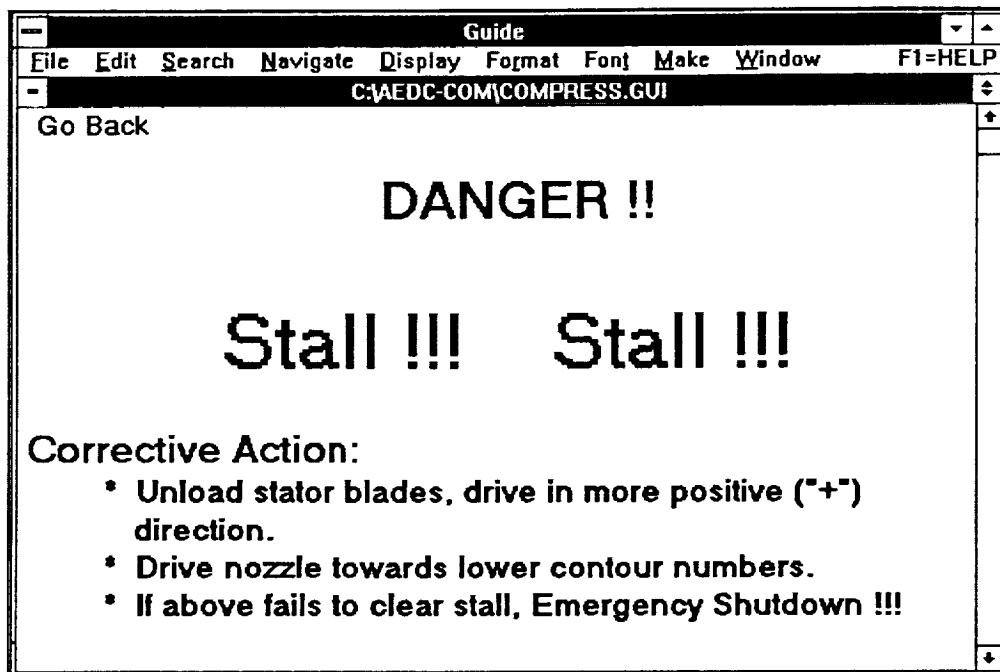


Figure 12. Graphic display for stall case.

APPENDIX A

LIST OF SOFTWARE

COMPRESS GUI	68610	02-01-91	L5-EXPER	<DIR>	01-15-91
GRAPHICS	<DIR>	01-16-91	RETURN	DAT	5 02-01-91
PLOT1	BAS	7555 01-18-91	COMPRESS	KNB	1152 01-18-91
PLOT1	EXE	20760 01-18-91	COMPRESS	PRL	1044 01-18-91
PLOT2	BAS	8420 01-18-91	RUNL5	BAT	62 01-15-91
PLOT2	EXE	22792 01-18-91	INPUT	DAT	39 02-01-91
EGADUMP	EXE	1067 06-03-89	(5 Files)		
(5 files)					
FEATURE	<DIR>	01-16-91	TESTDATA	<DIR>	01-17-91
AMPLITU9	BAS	3754 01-18-91	A1306-10	FRF	3860 06-05-90
AMPLITUD	EXE	39788 01-18-91	A1306-11	FRF	3860 06-05-90
AMPLITUD	BAS	3015 01-18-91	A1306-12	FRF	3860 06-05-90
FREQ	DAT	99 07-16-90	A1306-13	FRF	3860 06-05-90
OUTPUT		477 02-01-91	A1306-14	FRF	3860 06-05-90
TESTFILE		54 02-01-91	A1306-15	FRF	3860 06-05-90
AMPLITU9	EXE	41122 01-18-91	A1306-16	FRF	3860 06-05-90
(7 files)			A1306-17	FRF	3860 06-05-90
			A1306-18	FRF	3860 06-05-90
NEURAL	<DIR>	01-17-91	A1306-19	FRF	3860 06-05-90
BACKPROP	NNT	1538 10-16-89	A1306-S1	FRF	3860 06-05-90
BKPSTD	INS	3717 10-16-89	A1306-S2	FRF	3860 06-05-90
BKPSTDPR	INS	3886 10-16-89	A1306-S3	FRF	3860 06-05-90
C3RBRB	NNA	430 01-18-91	A1306-S4	FRF	3860 06-05-90
C3RBRB	NNB	191 09-13-90	C1706-10	FRF	3860 05-31-90
C3RBRB	NND	4716 01-16-91	C1706-11	FRF	3860 05-31-90
C3RBRB	NNR	3777 02-01-91	C1706-12	FRF	3860 05-31-90
DEFAULT	NNT	240 10-16-89	C1706-13	FRF	3860 05-31-90
DISPLAY	DG	16520 10-16-89	C1706-14	FRF	3860 05-31-90
NWE	EXE	279511 12-12-89	C1706-15	FRF	3860 05-31-90
NWORKS	HLP	111894 10-16-89	C1706-16	FRF	3860 05-31-90
NWORKS	MSG	16763 10-16-89	C1706-17	FRF	3860 05-31-90
ULOTUS	EXE	59492 10-16-89	C1706-18	FRF	3860 05-31-90
USERIO	EXE	16148 10-16-89	C1706-19	FRF	3860 05-31-90
VGA11	DG	7772 10-16-89	(24 Files)		
VGA12	DG	8528 10-16-89			
CALL	BAT	24 01-22-91			
CONVERT	BAS	768 01-18-91			
CONVERT	EXE	37468 01-18-91			
(19 files)					
PATTERN	<DIR>	01-28-91			
COMPTEST	EXE	38502 01-29-91			
A1306N21	ASC	4844 08-22-90			
A1306N31	ASC	4844 08-22-90			
C1706N2	ASC	4835 01-27-91			
C1706N1	ASC	4819 01-27-91			
C1706N3	ASC	4826 01-27-91			
A1306R11	ASC	4851 08-23-90			
A1306R31	ASC	4846 08-23-90			
A1306R21	ASC	4843 08-23-90			
A1306R01	ASC	4855 08-23-90			
A1306R61	ASC	4833 08-23-90			
A1306R71	ASC	4837 08-23-90			
TRACE	DAT	432 02-01-91			
CONVERT	BAS	768 01-28-91			
CONVERT	EXE	37468 01-28-91			
PATTERN	BAT	36 01-28-91			
COMPTEST C		8888 01-29-91			
(17 Files)					